One approach to control of a neural network with variable signal conductivity

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Abstract

The article focuses on a new extent to synthesize a control strategy of learning of a special artificial neural network with variable signal conductivity. The purpose of the research is to create new control strategy based on analysis of the neural network error signal. Also an approach to compute this control strategy is presented. The main result is contained in the necessity to realize the control strategy on the basis of preliminary training of the neural network with specific techniques. Also a crucial trajectory of the network's error decreasing is given in the article. The trajectory may be computed using signal processing methods.

Keywords: neural networks; control; signal processing; preliminary training

1. Introduction

Artificial neural networks are well known in application to transport planning, scheduling etc. Some papers are based on Hopfield's classical neural network with minimization of the energy function [1,2]. In [3] authors propose a hybrid scheme with the Hopfield's network and some heuristic methods to create timetable of CPU load. In [4] authors solve some transport problem by the multilayer perceptron with one hidden layer. All these works are not dedicated to creating the timetable with complex analysis of transport constraints. Besides all of these networks are not being trained with rigor methods. Moreover in [5,6] an approach to consider the neural network's teaching as an optimal control problem is presented. Hence in this paper authors are going to present an attempt to set the problem of rational control of the special neural network which solves rail scheduling problems.

2. The object of the study

The object of our analysis is a special neural network with variable signal conductivity described in [7]. Its topology is given in fig.1

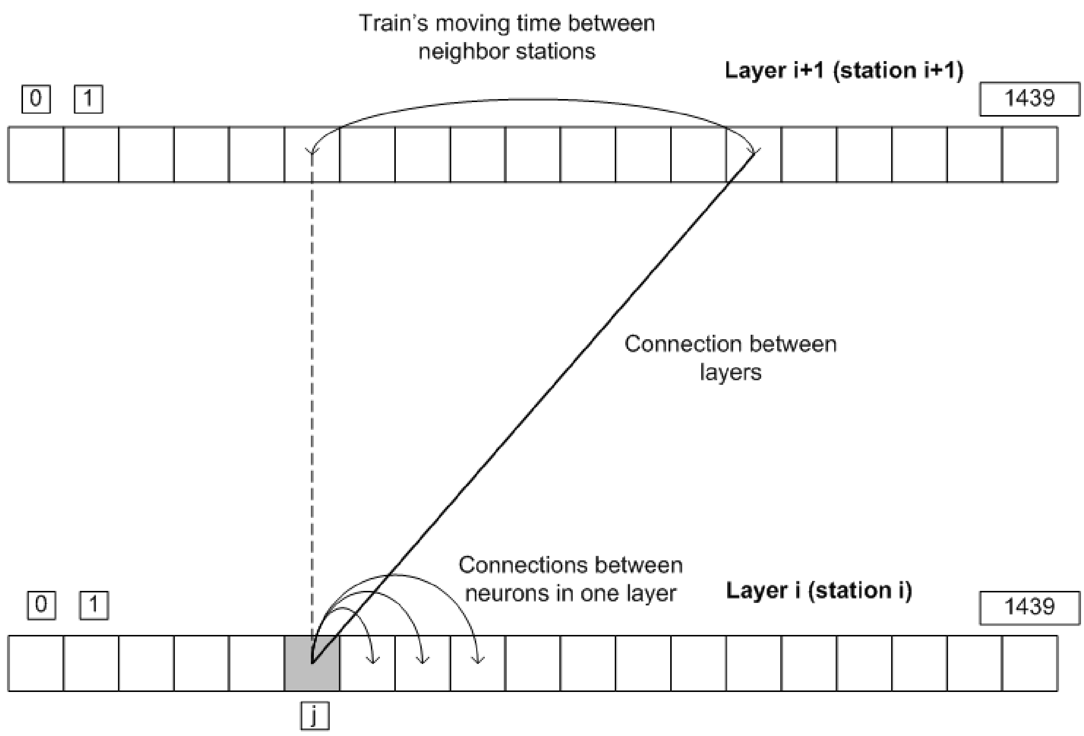

Fig.1. The architecture of the special neural network.

The number of stations is equal to the number of layers, every layer consists of 1440 neurons (it is equal to the number of minutes in the period of 24 hrs.) and every neuron is connected with the set of neighbor neurons both in the same and in the next layer in the manner of no train crashes. Inputs of the first border layer are time marks (minutes) of train departures, outputs of the second border layers are time marks (minutes) of train arrivals. Functioning of the neural network is being characterized by the error function computing special sum of time differences between desired and real outputs.

Physical sense of the architecture is as follows: every pair of active neurons in neighbor layers with active connection corresponds to signal conduction between these layers. And after selecting all the signal trajectories and printing them on the paper we'll get a variant of a train schedule created by the artificial neural network during its training process.

3. Methods

In particular case when the error function could be described as sum of sinusoidal-based harmonics with different frequencies and amplitudes we may use the results obtained in [8]. In general case we are not sure in this signal error representation. Typically the dynamics of the error function looks like in fig.2

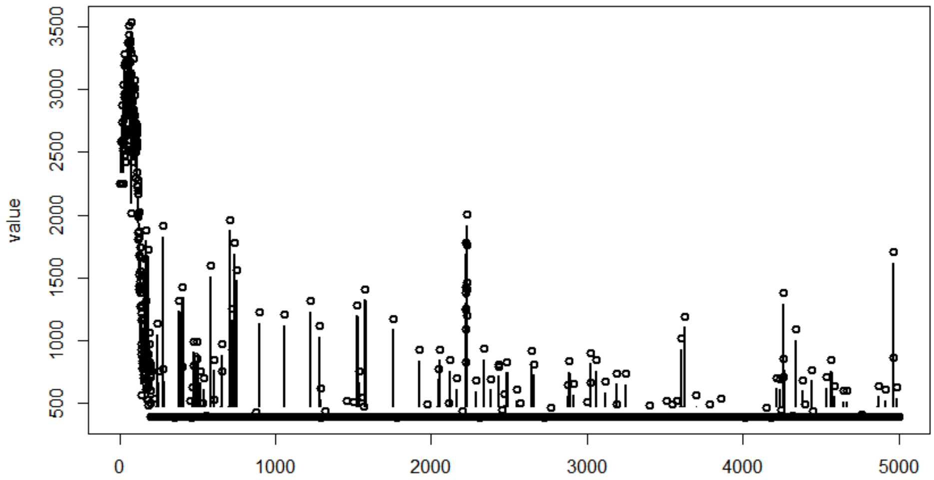

Fig.2. One example of error function.

To analyze the behavior of the error function we plot its autocorrelation function (fig.3).

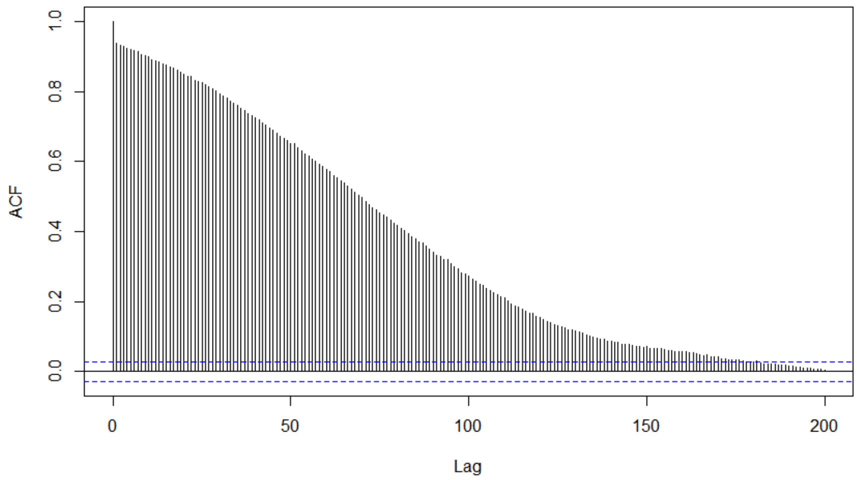

Fig.3. ACF of the error function.

It gave us an assumption that it is possible to decompose the signal. The goal of this decomposition is to filter the main components of the error function. After filtering we should try to implicate the decomposition for a rational control scheme to train the network.

According to the useful practice in stochastic market signal processing we have successfully implicated LOESS techniques [9] to decompose the signal of the neural network error function. The analyzed signal, as we discovered, consists of three perceptible components: a trend part, a periodic signal and the irregular components.

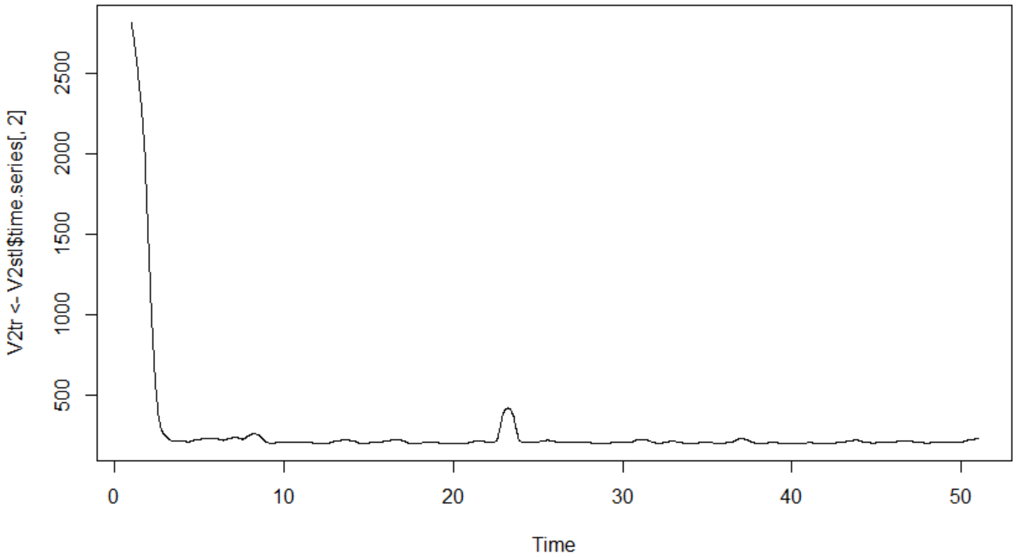

Fig.4. An example of STL-decomposition of the error function (trend).

The trend curve of the neural network error function provides guides for synthesis of the rational control.

4. Discussions about ways of control implementation

During the research authors have planned, realized and analyzed several series of computational experiments with variable key parameters of the neural network functioning including initial trainspeed, desired mean of the error, number of trains to scheduling etc. It is set that we have stable and iterative character of error function view (fig.2), trend function view (fig.4). So we conclude that we should find rational control of the neural network based on this curves (fig.4).

In consideration of the enormous quantity of links between neurons it is impossible to solve the control problem in terms of dynamics of every neuron link (and the system of differential equations). So it is potentially useful to apply some special techniques to simplify and generalize control influence like:

- Pre-amplification of the bundle of links in the concrete areas of the neural network;
- Pre-diminution of the bundle of links which are rather useless to desired trajectory of signal distribution (e.g. the links which may create too earlier or too later arrivals etc.);
- Simultaneously pre-amplification and pre-diminution of the links;
- Mutation of links' weights in bounded area;
- Swap of weights between the links of selected pair of neurons.

Another way to invent the control strategy is implementation of inverse general neural network control.

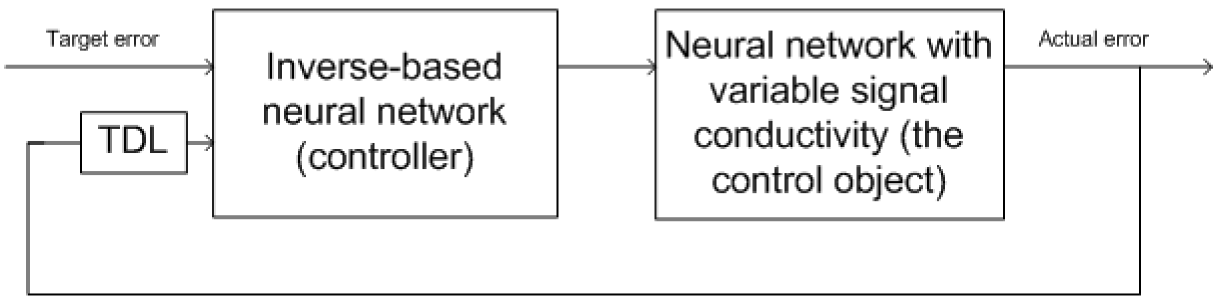

Fig.5. A principal scheme of inverse-based neural network control.

The main idea of the scheme given in fig.5 is as follows. We realize a control strategy for the neural network with variable signal conductivity (which is a controllable object) using another neural network (which is a controller). We have a target error curve (fig.4) and we know all statements of every weight per every moment so we may represent every weights change like a control step act. In epoch *(k-1)* we know all the picture of weights changes and hence the total of used control acts. Also we know the target level of the error function in epoch number k and the actual level of the error function in epoch k. So we may describe this situation as:

$$U(k-1) = f(E_k, E_k^t) \quad (1)$$

where:

$k-1$ is a number of previous epoch,

k is a number of current epoch,

E_k is an observable meaning of the error function

E_k^t is a target meaning of the error function given by STL-decomposition

$U(k-1)$ is the set of used control acts,

f() is a reaction of the inverse-based neural network.

An equation (1) describes the inverse-based neural network training mode.

In the work circuit given in fig.5 we feed into the inversed neural network's input the target error in *(k+1)* epoch and actual error in current epoch. The output of the inversed neural network should be interpreted as the control signal applicable to the neural network with variable signal conductivity. The last described scheme will work properly if the inversed-based neural network is trained relevant to behavior of the control object.

These issues are prospectively attractive tasks and things to be investigated and discussed.

5. Conclusions

1. To improve existing training methods of the neural networks with variable conductivity of signals it is possible to use some rigor mathematical disciplines. The theoretical basis for it can be synthesized of the settlements from Theory of Optimal Control and Theory of Signal Processing. It allows us to construct various transport timetables in more effective way.
2. Each neural network despite the kind of solved problems should be detected and registered. Its error signal should be processed and filtered to distinguish main component from signal series.
3. According to the trend component of the signal the system of weights and links of the neural network must be modified using one of techniques described above.
4. It worth sharing a new control scheme working with an inverse-based neural network control. The specific feature of the considered task is the neural network as a controllable object. This representation in innovative. In classical case we have is a technical or a chemical systems described by its evolutionary equations and a neural network as a controller.

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